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# Does hot money in equity flows affect emerging stock markets?

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## Abstract

I investigate the influence of hot money in equity flows from the U.S. to twelve Emerging Markets (EMs) on the local stock markets over the period from January 1993 to December 2013, including both crisis and non-crisis periods. I identify *de facto* hot money as the temporary component of equity flows, and conduct Vector AutoRegressive models (VARs) using monthly data on emerging markets with Granger causality test and impulse response analysis. I show that hot money in equity flows from the U.S. to emerging markets does have a significant impact on the local stocks, but the local stock market has little effect on hot money. The findings suggest a new factor regarding equity predictability and profitability which both the investment advisors/consultants and policymakers may take into account.

**Keywords:** Hot money; Equity flows; Emerging stock markets.

**JEL classification:** E44; F20; F34; G1.

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## 1. Introduction

Along the path of financial globalisation, Emerging Markets (EMs) have witnessed a sharp increase in international capital flows. According to a survey released by the International Monetary Fund (2011a, b), the annual amount of foreign private net capital flowing into EMs was about 11 billion and 22 billion USD in the 1970s and 1980s respectively, which increased dramatically to 150 billion USD over the period from 1991 to 1998, and plunged to 58 billion USD between 1998 and 2002 due to the 1997 Asian Financial Crisis. After that, the volume of equity inflows to EMs resurged until 2007, which was followed by a significant reversal in 2008-2009 during the “flight to safety” during the late 2000s Global Financial Crisis (Caballero and Krishnamurthy, 2008). As major advanced industrial countries launched the quantitative easing schemes during the late 2000s Global Financial Crisis (GFC), speculative capital flows (or *hot money*), have relocated to the EMs with higher interest rate, which might bring negative effects to the local stock market stability (Martin and Morrison, 2008; Korinek, 2011).

*Hot money*, characterized by high sensitivity, high mobility and reversibility, refers to the flow of capital from one country to another in order to earn a short-term profit on interest rate differences, anticipated exchange rate shifts or equity premium (Chari and Kehoe, 2003; Fuertes et al., 2016). They may become a destabilizing force to emerging market economies within an undeveloped financial system (Martin and Morrison, 2008). In the wake of the late 2000s GFC, a large number of emerging market economies, including South Korea, Thailand, Indonesia, Taiwan China, and Brazil have moderated the pace of liberalisation successively and turned to re-impose capital controls with various forms (International Monetary Fund, 2011a, b; Ostry et al., 2010). The current advocacy on capital controls in EMs implicitly builds on the presumption that foreign investors destabilize the local financial markets but lacks of empirical evidence, probably because a well-defined estimating method of the “hot money” inflows amount for a certain country during a period has only become available very recently (Fuertes et al., 2016).

Given the gap in the extant literature, I investigate the question of the interrelationship between hot money in equity flows and the local stock returns. Subjects in my empirical studies are 12 emerging market economies that are carrying greater weight in the global economy both in terms of GDP and CAP (market capitalization). Following Fuertes et al. (2016), I identify *de facto* hot money as the temporary component of equity flows from the U.S. to emerging market economies, by state-space model via Kalman filter using monthly data over a relatively long time span from January 1993 to December 2013. After obtaining data for hot money in equity flows, I conduct Vector Autoregressive models (VARs) to explore the interrelationship between hot money in equity flows and the local stock returns using monthly data on emerging markets with Granger causality test as well as impulse response analysis. The VAR models in a strand of literature in this area such as Froot et al. (2001), Dahlquist and Robertsson (2004), Richards (2005), Froot and Ramadorai (2008), Jinjarak et al.(2011), Yan (2015), and Yan et al.(2016).

I find that massive hot money in equity flows from the U.S. to emerging markets does yield a significant impact on the local stock markets, but the local stock market does not have a statistically significant effect on hot money. For investment advisors/consultants, hot money can be a clue for them to predict the trend of the stock market. They should pay more attention to the composition rather than quantity of cross-border equity flows, especially hot money.

The remainder of this paper unfolds as follows. I present the relevant literature and data in Section 2 and 3, respectively. Sections 4 and 5 provide the empirical results from state-space models and VAR models, respectively. The last section concludes.

## **2. Background Literature**

This paper closely relates to two strands of the literature. The first one is the strand of literature investigating the impact of hot money or international capital flows on local markets, while the second one is the strand of literature studying the “drivers” of hot money or international capital flows.

Despite an extensive body of research, there remains a heated debate in the literature on the benefits and costs of financial globalization (for surveys, see Stulz, 2005; Henry, 2007; Kose et al., 2010; and Rodrik and Subramanian, 2009). An often-heard critique of financial openness is that the temporary part of capital flows, often termed “hot money”, destabilizes local asset markets (see, e.g.: Korinek, 2011, Fuertes et al., 2016). While the inflows of “hot money” builds up gradually over time, the outflows happen *en masse* and simultaneously, with each player in asset markets, such as shareholders in the stock market, struggling to be the first to exit (for a recent survey, see, Kawai and Takagi, 2010).

On the one hand, some researchers, especially the neoclassical school, argue that financial globalisation and international capital inflows boost economic growth (Bekaert et al., 2005). For instance, Bhagwati (1998), Edison and Reinhart (2001) and Kose et al. (2009) argue that there is a positive influence of capital account openness on real variables (such as investment, economic growth, etc.). Through event study techniques, Henry (2000) notes that there is a temporary speed-up in the growth rate of private investment following stock market liberalisation for major emerging markets. Henry (2007) adopts “policy-experiment approach”, which considers the growth-enhancing effect of a discrete change in capital account policy as a one-time event and makes arguments based on the results that stock market liberalisation is positively associated with growth and investment. Rather than only emphasizing the direct capital flows, literature in this area highlights collateral benefits of capital flows, such as developments in domestic financial sectors (see Levine, 2005; Mishkin, 2006; 2009), improvements in institutions (see Stulz, 2005) and macroeconomic policies (Gourinchas and Jeanne, 2006).

On the other hand, other literature such as Grilli and Ferretti (1995), Rodrik (1998), and Prasad et al. (2003) find little evidence supporting the argument that economic growth is positively correlated with capital account liberalisation. Calvo (1998) report that international capital inflows bring about negative effects like the instability of financial environment, rising prices, deterioration of trade conditions and so on. Jeanne et al. (2012) run over 2300 regressions named a “meta-regression” approach, which employs six *de jure* and *de facto*

measures of financial liberalisation, attempting to figure out whether capital account openness affects output growth or not. They reach a conclusion that little conclusive evidence backs up the growth-enhancing role played by capital mobility, and it is essential to establish a framework that achieves international consensus for desirable capital controls. With a number of emerging market economies broke out a series financial crises after the late 1980s, some economists believe that enormous amounts of capital movements after opening a capital account may become a source of the local macroeconomic instability and enhance fragility of finance. A flood of capital inflows drives credit booms, asset bubbles, and high foreign debt. As a result, a financial crisis can be detonated easily when capital flows suddenly stop or reverse (Kaminsky et al., 1999). More recently, Caballero and Krishnamurthy (2008) and Korinek (2011) have studied the phenomenon of “moving bubble” that when one country or sector in the world economy experiences a financial crisis, hot money will flow into another less constrained countries or sector.

A subset of this strand of literature distinguishes different types of international capital flows (Sarno and Taylor, 1999a, b; Fuertes et al., 2016). They divide cross-border capital into five types (portfolio equity, debt, official capital, FDI and bank flows), and conduct state-space models to gauge the relative importance of the temporary component (“hot money”) in every form. Their conclusions are that the temporary component or “hot money” plays a key role in various categories of international capital flows, and these categories have suffered a high degree of reversibility, which provides indirect evidence for the view that these categories of capital flows act as a plausible channel for crisis transmission. None of these papers, however, indeed examines the impact of hot money on local equity markets.

The second literature to which this article is related studies the other side of the problem, that is, the effect of the local stock returns on hot money in equity flows. Mainstream literature distinguishes the drivers of short-term capital inflows to emerging markets into the “pull” factors (economic fundamentals of recipients) and “push” factors (international economic factors outside recipients). For instance, Taylor and Sarno (1997) indicates that the U.S. federal funds rate is the most important factor that affects short-term debt capital inflows into

emerging markets while other “push” factors and “pull” factors contribute equally to the short-term equity capital or the long-term equity capital inflows. Kim (2000) has shed light on the reason for capital movement in Mexico, Chile, South Korea and Malaysia by adopting method of structural decomposition and concludes that “push” factors are the driving force. Froot et al. (2001) explore not only the correlation between foreign investor inflows and contemporaneous returns but also the association between equity inflows and future returns in emerging markets. They suggest that it takes local equity prices a few days to drift after the trading of foreign investors, which reports a protracted impact instead of a contemporaneous impact of foreign flows on equity prices. Richards (2005) examines the trading behaviour of foreign investors in six Asian emerging equity markets by VAR and discovers that net foreign inflows are positively related to the same-day local equity returns. Focusing on the role played by foreign exchange, Yan (2015) exploits the interaction between equity flows and stock returns and provides some new evidence on foreign investors' trading behaviour and their price impact, and finds that the bidirectional causality is plausible; that is to say, equity flows have a positive impact on equity returns and vice versa. Although none of these previous papers studies whether and how local equity markets drive the hot money, recent literature (such as Fuertes et al., 2016) provides me an opportunity to do so.

### **3. Data**

I collect monthly bilateral capital outflow and inflow data in US\$ million over a time span from January 1993 to December 2013 from the U.S. Treasury International Capital (TIC) database. “Gross purchases by foreigners” and “gross sales by foreigners” are classified as U.S. sales and U.S. purchases respectively in the International Capital Reports of U.S. Treasury Department. The data are collected and presented from the perspective of the foreign parties to the transactions. By definition, “gross purchases by foreigners” are gross sales by U.S. residents. Similarly, “gross sales by foreigners” are gross purchases by U.S. residents. A positive difference indicates net foreign purchases from U.S. residents (U.S. capital inflow) while a negative difference indicates net foreign sales to U.S. residents (U.S. capital outflow).

The twelve emerging markets in my sample are Argentina (AG), Brazil (BR), Mainland China (CH), Chile (CL), Indonesia (ID), India (IN), South Korea (KO), Mexico (MX), Malaysia (MY), Philippines (PH), Thailand (TH), and Taiwan China (TW). There are eight Asian markets: Mainland China (CH), Indonesia (ID), India (IN), South Korea (KO), Malaysia (MY), Philippines (PH), Thailand (TH), and Taiwan China (TW), and four Latin American markets: Argentina (AG), Brazil (BR), Chile (CL), Mexico (MX). Daily data for such a large number of countries are not available (Yan, 2015).

These are the main markets covered by the previous literature. The sample size of 12 markets is large enough to provide results that are potentially fairly general, yet is small enough to allow more attention to market-specific analysis and presenting results market-by-market in an intelligible way than might be impossible in datasets with a larger number of markets. My sample markets have been studied in earlier literature. For example, Richards (2005) have a look at Indonesia, South Korea, Philippines, Thailand and Taiwan China. Fuertes et al. (2016) and Yan et al. (2016) include all these market as a subsample of their studies. These markets are of vital importance in the global economy no matter in terms of Gross Domestic Product or the amounts of capital flows.

I scale the observed equity flows by U.S. consumer price index (CPI) to eliminate the impact of inflation effects. I take the price in 1993 as the price of the base year in the U.S. My results do not qualitatively change when I repeat the analysis process based on the un-scaled short-term equity flows data. CPI data are obtained from Datastream.

Following Sarno and Taylor (1999a, b) and Fuertes et al. (2016), I decompose the observed equity flows from the U.S. to 12 EMs into unobserved permanent and temporary components and identify “hot money” in equity flows as the temporary component via deploying state-space models using Kalman filter algorithm.

Bloomberg is used to collect data for emerging market stock price indices in US\$ for all of my sample countries. Then I calculate the monthly returns of the equity market indices in EMs, a proxy for equity returns, which can be approximately estimated by taking the



logarithm of stock indices.

#### **4. Identifying hot money**

I report the results from state-space models, which themselves are detailed in the appendix, in Table 1. The maximum value of determination  $R^2$  is 0.492 while the minimum coefficient is 0.255. All Q-ratios for the permanent component are extremely low while those for the temporary component are much larger, which shows that the irregular or AR component explains significant portions of disturbance variance. My results are in line with that of Fuertes et al. (2016), the dynamics of equity flows can be mainly interpreted by the temporary component. Namely, equity flows from the U.S. to twelve emerging markets (EMs) from 1993 to 2013 have been dominated by the temporary component (“hot money”).

I graph the unobserved temporary component ( $v_{it} + \varepsilon_{it}$ ) estimation of equity flows generating from Kalman filter state space decomposition. To be specific, Figure 1 plots the time-series of the unobserved temporary component (or “hot money”) in equity flows from the U.S. to 8 Asian EMs while Figure 2 reveals the decomposition results of 4 Latin American EMs.

There are some interesting findings. First, the past decades have witnessed a remarkable increase in the scale of hot money from the U.S. to emerging stock markets. Second, there is a statistically significant difference between Asia and Latin America in the size of “hot money”. It varies markedly across Asia while not that much across Latin America over the sample period. Most noticeably, Mexico differs significantly from the other three emerging markets as can be seen from the graphs. Perhaps geographic factors and the close co-operative relations between Mexico and the U.S. shape it. Third, “hot money” inflows to Asia and Latin America increased obviously in volatility in the 21st century, especially in the recent decade. Clearly, “hot money” has experienced a dramatic fluctuation before and after the 2008 global financial crisis.

Promoted by reductions in stock market investment barriers, equity flows to emerging markets have increased in volume as well as in volatility after the Asian financial crisis.

Nevertheless, following their 2007 peak (\$205 billion), they reversed suddenly in 2008-2009 affected by the Global Financial Crisis that sparked the flight-to-safety movement. Under the background of quantitative easing in advanced economies, investors treat EMs as a fruitful destination with higher interest rate. Therefore, equity inflows to EMs rebounded strongly in 2010 and 2011. Taking Mainland China as an example, there was only small-scale “hot money” before 2003 but the magnitude increased basically after 2005. In fact, the expectation of RMB appreciation had risen since July 2005 when RMB exchange rate reform was implemented. It coupled with expansionary monetary policy and even four rounds of quantitative easing in the U.S., leading to more “hot money” flooded into China for arbitrage.

## **5. The relationship between hot money and local equity markets**

On the base of VAR framework, I take advantage of standard tools to test whether the model agrees with the initial assumption and economic implications so that I can obtain reliable interpretations of the interaction between hot money and the local stock returns. Section 5.1 specifies my VAR model, while Section 5.2 reveals VAR coefficient results. Section 5.3 and Section 5.4 present the findings from Granger causality tests and the impulse response analysis, respectively.

### **5.1 VAR models**

I do not conduct seasonal adjustment on my main variables, as these variables show little remarkable seasonal variation. I start the analysis of economic time series from the stationarity tests to get rid of the spurious regression. In this paper, I adopt the Augmented Dickey–Fuller test (ADF) to test the stationarity of two time-series variables, “hot money” and “stock market returns”.

Table 2 shows that both test statistics for “hot money” and “stock market returns” are larger than critical values under the 90%, 95% or 99% likelihood levels. Hence, I reject the null hypothesis that these series have a unit root. Put differently, I treat these series as stationary.

I primarily propose two hypotheses before examining the interrelationship between hot

money in equity flows and the equity returns in EMs. The first is that hot money in equity flows has an influence on emerging stock market returns, which is inspired by the views drawn from Kohli (2001). Kohli (2001) conducts the empirical analysis on Indian data and puts forward that the changes of stock index in India are correlated to international capital flows. Nevertheless, the internal mechanism of the impact of hot money on the local stock market is still not clear. Although practitioners widely accept the opinion that the impact is a consequence of foreign investors' technology or information advantage, there is not much empirical evidence to support it. If the standpoint above is plausible, then I expect a positive (negative) excess return when hot money flows in (out) of emerging markets.

Since the 1990s, mainstream literature has made arguments on the motivation of the U.S. international equity investments. Different from the previous views that investors invest their capital in emerging markets to rebalance their international portfolios, they argue that the U.S. investors are motivated by chasing returns. Hot money, aimed at earning a short-term profit, is characterized by high sensitivity, high mobility and reversibility, which makes it a dangerous tool for portfolio-balancing strategy. In this sense, hot money is more likely to be driven by return-chasing strategy. Taking this into consideration, I set up the other hypothesis, the reverse causality between hot money and stock returns, that is, stock returns in EMs are dominant drivers of equity inflows, as suggested in some literature. For example, event study techniques help to come to the conclusion that there is a temporary speed-up in the growth rate of private investment following stock market liberalisation for major emerging markets in Henry (2000). Richards (2005) examines the trading behaviour of foreign investors in six representative Asian emerging equity markets and discovers that net foreign inflows are positively associated with the same-day local equity returns. Edison and Reinhart (2001) carry on the quantitative analysis of the consequences of capital controls in Brazil, Thailand, and Malaysia based on daily data. They conclude that capital controls result in high-interest rates, in turn, lead to adjustment of asset prices in Malaysia while they fail to find a significant impact of capital controls on asset prices in Brazil and Thailand. If the hypothesis holds, I conjecture that a positive correlation between past stock returns in EMs and current hot money inflows will be observed.

After obtaining data of hot money, I utilize the vector autoregressive modelling approach to analyse the interrelationship between hot money and the local stock returns. The reason why I introduce VAR models is that they provide us a general method to evaluate bi-directional causality, that is, on the one hand, hot money may cause stock prices rise or fall, on the other hand, the stock returns would drive hot money flows. The VAR I estimate can be modeled as

$$Y_t = C + \pi_1 Y_{t-1} + \pi_2 Y_{t-2} + \dots + \pi_k Y_{t-k} + \mu_t \quad (1)$$

where  $\mu_t \sim \text{i.i.d.} N(0, \Omega)$

I can display VAR model in a compact form for  $t=1, 2, \dots, T$ , where  $Y_t$ ,  $C$  and  $\mu_t$  are  $2 \times 1$  column vectors, and  $\pi_i$  is a  $2 \times 2$  coefficient matrix.

$$Y_t = \begin{bmatrix} \text{Hot Money}_t \\ \text{Stock Return}_t \end{bmatrix}, \quad C = \begin{bmatrix} C_1 \\ C_2 \end{bmatrix}, \quad \mu_t = \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \end{bmatrix}, \quad \pi_i = \begin{bmatrix} \pi_{11,i} & \pi_{12,i} \\ \pi_{21,i} & \pi_{22,i} \end{bmatrix} \quad i=1, 2, \dots, k$$

The unknown parameters  $C$  is the constant intercept term,  $\pi_i$  is the coefficients of the endogenous variables, and  $\mu_t$  is the disturbance vector. I use aggregate monthly data of hot money and equity returns across all emerging market economies, covering a sample period from 1993 to 2013. Hot Money is the temporary component of equity flows from the U.S. to EMs scaled by the local equity market capitalization; Stock Returns are a monthly percentage of value-weighted returns on emerging stock indices

## 5.2 VAR model coefficients

I use the Akaike information criterion (AIC) and Schwartz-Bayes criteria (SC) to specify the appropriate lag length of the VAR model, which turns out to be a lag length of one. The VAR model employed eventually can be written as

$$\begin{bmatrix} \text{Hot Money}_t \\ \text{Stock Return}_t \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \end{bmatrix} + \begin{bmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \pi_{22} \end{bmatrix} \begin{bmatrix} \text{Hot Money}_{t-1} \\ \text{Stock Return}_{t-1} \end{bmatrix} + \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \end{bmatrix} \quad (2)$$

Table 3 reports the coefficient estimates of vector autoregression with one lag for each endogenous variable. Clearly, past hot money has a significant positive explanatory power on

stock returns in EMs since the t-statistics is 4.3238, much larger than the critical value at 1 percent statistical significance level. However, lagged stock returns have little forecasting power for current hot money (t-statistics is only 0.4778). The following Granger-causality tests can confirm the results.

### ***5.3 Granger-causality tests***

Some economic variables are significantly correlated with each other but not necessarily meaningful. Causality is one of the most difficult issues in finance, economics as well as other social sciences. One possible way to deal with it is the so-called Granger-causality, which is a statistical measure of causality based on prediction. A variable  $X_1$  "Granger-causes" another variable  $X_2$ , if and only if the past values of  $X_1$  contain information which helps predict  $X_2$  beyond the past values of  $X_2$  only (for details, pls refer to Yan et al., 2016 or others).

Following the extant literature, I carry on Granger-causality tests to explore whether the variation of hot money in equity flows (stock returns of EMs) does contribute to the change of stock returns of EMs (hot money in equity flows).

According to Table 4, hot money in equity flows only has unilateral Granger causality with stock returns in emerging markets, that is, hot money is the Granger causality of stock returns and stock returns is not the Granger causality of hot money. In other words, changes of stock returns do not yield a significant impact on the flow of hot money.

### ***5.4. Impulse response analysis***

Moreover, I ensure the stationarity of my VAR model as all eigenvalues of the coefficient matrix lie within the unit circle. I adopt generalized impulse response function to illustrate how each variable in the model responds to shocks as time goes on, as Pesaran and Shin (1998) have demonstrated that the generalized impulse response function is invariant to the ordering of the variables in the VAR. Figure 3 show the impact of one-standard-deviation shock to hot money in equity flows on equity market returns and the influence of stock

returns bring to hot money.

The vertical axis represents changes in hot money (or stock returns), while the horizontal axis stands for lag intervals of shocks (monthly). The solid lines are impulse response function, and the dashed line indicates the double standard deviation band. Obviously, both of “hot money” and “stock returns” would react strongly to the shocks on themselves and the response patterns share a similarity. The reaction extent of hot money itself at the first month is the greatest when given a positive shock. Then, the impact decreases gradually and vanishes eventually. It indicates that short-term equity flows quickly pool into EMs from the U.S. for short-term profits and promptly withdraw from EMs.

As can be seen from further observation on cross response function, a positive shock of hot money by the size of one unit standard deviation in the current period has a positive impact on stock returns within the following two months, and reaches a peak after one and a half months. However, this impact begins to decline after that until disappear. It demonstrates that giving hot money a positive shock; it will bring the same impact on stock markets for about 1-2 months. Namely, hot money inflows effectively promoted the short-term growth of the local stock markets. The other way round, it is clear from the response of hot money to stock returns shocks that a positive shock to stock returns would bring a light positive response to hot money with short-term persistence effects. In other words, hot money is insensitive to the innovation of the local stock returns and the current stock market boom becomes less appealing to hot money inflows over time.

I find an insignificant effect of stock returns on hot money in equity flows, which aligns with the previous literature that attributes the reason why short-term foreign equity flows enter emerging economies to “push” factors. Taylor and Sarno (1997) suggest that external factors other than U.S. interest rate and “pull” factors make an approximate contribution to short-term and long-term equity capital inflows. Inspired by several previous academic papers (e.g., Chohan et al., 1998) that classify emerging economies into two groups as Asia and Latin America when discussing factors affecting international capital movements, I repeat empirical analysis to Asia and Latin America EMs respectively. It turns out that the

heterogeneity in terms of my results is not that prominent across countries, and my previous conclusions are reinforced. Table 5 reports the results from Granger causality tests while Figure 4 and Figure 5 provide the details of impulse response analysis.

#### **5.4. Robustness**

I have done several additional tests to make sure the robustness of my results. First of all, I use the local currency equity indices instead of the USD MSCI indices to construct equity returns, which is in line with the insights of Yan (2015). The results are reported in Table 6, from which we can see that the main results are qualitatively unchanged. The economic magnitude of the impact of hot money on stock returns has been substantially reduced, from 0.0142 to 0.000108, while statistically significant as before with a t-statistic of 4.02768, which is in line with the intuition of Yan (2015).

Moreover, although this paper demonstrates that hot money is correlated with future returns, other variables could be influencing stock returns. I thank a referee for this comment. I have tried to control the main exogenous variables in the literature and find the results unchanged, if not stronger. For instance, table 7 reports the pooled coefficients estimates of one-month lagged hot money and stock returns for all the markets in my sample in aggregate with effective fed fund rates, the VIX from CBOE, the TED spread as control variables. The coefficient of lagged hot money in the stock return equation increased from 0.0142 to 0.017961, with a t-statistic of 2.56495. We have also tried other combinations in Yan et al. (2016) and find similar results.

Last but not the least, given the data covers a long period with both crisis and non-crisis years, it might be interesting to implement an analysis on the impact of the latest financial crisis. I thank the referees for this comment. Table 7 reports the pooled coefficients estimates of one-month lagged hot money and stock returns for all the markets in my sample in aggregate over the crisis periods. The crisis period is defined from January 2007 to December 2013, and from August 2007 to December 2013, in panel A and B, respectively. I confirm the previous results that past hot money has a significant positive explanatory power on stock

returns in EMs, but lagged stock returns have little forecasting power for current hot money. More interestingly, the economic magnitude of the impact of hot money on local equity markets is larger during crisis period (from 0.0142 to 0.020864), and even larger when the crisis is going on (0.022813).

Overall, I find that hot money have a significant impact on the local stock markets, but not the other way around.

## **6. Conclusions**

In the wake of the late 2000s Global Financial Crisis (GFC), the impact of hot money on the emerging markets (EMs) has come again under intense scrutiny. The resurgence of global capital flows, in the aftermath of Quantitative Easing (QE) programs in the U.S., has brought back proposals for a Tobin tax on cross-border capital flows, and has led the IMF to publicly abandon its position that capital controls are inappropriate for most countries. Several EMs, including Brazil, Taiwan China, South Korea, Indonesia, and Thailand have recently re-adopted capital controls. These advocating capital controls implicitly build on the presumption that foreign investors destabilize local financial markets, while the international finance literature has provided scarce evidence on this subject. This paper fills this gap.

Perhaps the most difficult issue is to gauge the actually amount of “hot money” during a specific period for a specific country. Following Fuertes et al. (2016), in this paper I identify *de facto* hot money as the temporary component of equity flows, using state-space models via Kalman filter algorithm.

The main part of this paper is the interrelationship between hot money in equity flows and the local stock returns. My empirical analysis indicates that massive hot money in equity flows from the U.S. to emerging markets does yield a significant impact on the local stock markets, but the local stock markets have little effect on hot money. For investment advisors/consultants, hot money can be a clue for them to predict the trend of the stock market. They should pay more attention to the composition rather than quantity of cross-



border equity flows, especially hot money.

One future direction can be to look at the hot money from the perspective of trust (e.g., Massa et al, 2015), since the emerging markets are typically low-trust markets while the advanced markets are usually high-trust ones. Due to this reason, it is plausible that the hot money in equity flows from the U.S. to the emerging markets is greatly trusted by the investors in the U.S. Hence, the international hot money is able to affect the emerging equity markets by both stock-picking and timing, as well as resist the attraction from the short-term fluctuations from the emerging equity markets. However, it is beyond the scope of this paper and I leave it as a possible direction for future research.

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**Table 1. State-Space Model for Net Equity Flows in EMs**

This table reports the results from state-space models for net equity flows, which are CPI-scaled capital flows in US\$ millions. A dash indicates that the component at hand is absent from the model.  $0 \leq Q\text{-ratio} \leq 1$  is the standard deviation of the each component over the largest standard deviation across components, computed from the variance-covariance matrix of disturbances. Column five reports the final level of the stochastic trend and its root mean square error (RMSE). The last column reports the  $R^2$ . The sampling frequency is monthly over the period from January 1993 to December 2013. The abbreviation of the country's name is listed as follows: Argentina(AG), Brazil(BR), Mainland China(CH), Chile(CL), Indonesia(ID), India(IN), South Korea(KO), Mexico(MX), Malaysia(MY), Philippines(PH), Thailand(TH), and Taiwan China (TW).

Cou ntry	Q-ratio( $\omega_t$ ) (Stochastic trend)	Q-ratio( $v_t$ ) (AR)	Q-ratio( $\varepsilon_t$ ) (Irregular)	AR(1) coeffi cient	AR(2) coeffi cient	Final level of stochastic trend [RMSE]	$R^2$
AG	0.000	0.202	1.000	1.754	-0.758	-0.655[0.226]	0.492
BR	0.000	0.809	1.000	0.774	--	3.487[0.026]	0.353
CH	0.000	0.569	1.000	0.688	--	-0.784[0.355]	0.404
CL	0.000	0.249	1.000	0.683	-0.116	-0.471[0.097]	0.467
ID	0.000	0.514	1.000	0.672	--	0.203[0.184]	0.391
IN	0.000	0.520	1.000	0.858	--	1.392[0.057]	0.423
KO	0.000	0.789	1.000	0.892	--	0.482[0.669]	0.372
MX	0.000	0.894	1.000	0.841	-0.177	-1.582[0.009]	0.353
MY	0.000	--	1.000	--	--	-0.067[0.511]	0.334
PH	0.000	0.480	1.000	0.848	--	-0.034[0.586]	0.404
TH	0.000	0.486	1.000	0.715	--	0.260[0.008]	0.397
TW	0.000	1.000	0.000	0.510	--	0.978[0.470]	0.255

**Table 2. ADF Unit Root Test Results**

The table reports the Augmented Dickey Fuller (ADF) test statistic for the null hypothesis of unit root (non-stationary) behaviour versus stationarity. The last three columns report critical values at 1%, 5% and 10% level, respectively. The sampling frequency is monthly over the period from January 1993 to December 2013.

series	t-Statistic	test critical values		
	ADF test statistic	1% level	5% level	10% level
hot money	-9.7063	-3.4565	-2.8730	-2.5729
stock market returns	-12.7423	-3.4564	-2.8729	-2.5729

**Table 3. Overall VAR Estimates**

The table reports the pooled coefficients estimates of one-month lagged hot money and stock returns for all the markets in my sample in aggregate. Left (right) panel results are for one-month lagged hot money (stock returns). The numbers in the second row (in italics) are *t*-statistics for the null hypothesis that the corresponding coefficient of hot money or stock returns is zero. The VAR coefficients and covariance matrix are estimated by OLS. The sampling frequency is monthly over the period from January 1993 to December 2013.

series	Hot Money		Stock Returns	
	coefficient	t-statistics	coefficient	t-statistics
Hot Money(-1)	0.4261	<i>7.2360</i>	0.0142	<i>4.3238</i>
Stock Returns(-1)	0.5253	<i>0.4778</i>	0.1527	<i>2.4881</i>
Intercept	-2.8044	<i>-0.3513</i>	0.3874	<i>0.8693</i>



**Table 4. Overall Granger Causality Tests**

The table reports F-statistics, P-value, and conclusion for the null hypothesis of ‘no Granger-causality’ either from stock returns to hot money, or from hot money to stock returns for all the markets in my sample in aggregate. The sampling frequency is monthly over the period from January 1993 to December 2013.

Null Hypothesis	F-Statistic	P-value	Conclusion
Stock Returns does not Granger Cause Hot Money	0.2282	0.6333	cannot reject
Hot Money does not Granger Cause Stock Returns	18.6951	2.E-05	reject

**Table 5. Granger Causality Tests for Asian and Latin American sub-groups**

The table reports F-statistics, P-value, and conclusion for the null hypothesis of ‘no Granger-causality’ either from stock returns to hot money, or from hot money to stock returns for two sub-groups in my sample. Panel A pertains to the sub-group of the Asian countries and Panel B to the sub-group of the Latin American countries. The sampling frequency is monthly over the period from January 1993 to December 2013.

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**Panel A: For Asia**

Null Hypothesis	F-Statistic	P-value	Conclusion
Stock Returns does not Granger Cause Hot Money	0.0761	0.7828	cannot reject
Hot Money does not Granger Cause Stock Returns	7.9431	0.0052	reject

**Panel B: For Latin America**

Null Hypothesis	F-Statistic	P-value	Conclusion
Stock Returns does not Granger Cause Hot Money	1.4001	0.2484	cannot reject
Hot Money does not Granger Cause Stock Returns	4.5646	0.0113	reject

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**Table 6. Overall VAR Estimates with local-currency stock returns**

The table reports the pooled coefficients estimates of one-month lagged hot money and local-currency stock returns for all the markets in my sample in aggregate. Left (right) panel results are for one-month lagged hot money (stock returns). The numbers in the second row (in italics) are *t*-statistics for the null hypothesis that the corresponding coefficient of hot money or stock returns is zero. The VAR coefficients and covariance matrix are estimated by OLS. The sampling frequency is monthly over the period from January 1993 to December 2013.

series	Hot Money		Stock Returns	
	coefficient	t-statistics	coefficient	t-statistics
Hot Money(-1)	0.420614	<i>7.17255</i>	0.000108	<i>4.02768</i>
Stock Returns(-1)	125.0191	<i>0.93336</i>	0.181007	<i>2.95875</i>
Intercept	-3.904870	<i>-0.48506</i>	0.008688	<i>2.36294</i>

**Table 7. Overall VAR Estimates with control variables**

The table reports the pooled coefficients estimates of one-month lagged hot money and stock returns for all the markets in my sample in aggregate with effective fed fund rates, the VIX from CBOE, the TED spread as control variables. Left (right) panel results are for one-month lagged hot money (stock returns) on the crisis period. The numbers in the second row (in italics) are *t*-statistics for the null hypothesis that the corresponding coefficient of hot money or stock returns is zero. The VAR coefficients and covariance matrix are estimated by OLS. The sampling frequency is monthly. The sampling frequency is monthly over the period from January 1993 to December 2013.

<b>Panel A</b>	<b>Hot Money</b>		<b>Stock Returns</b>	
	coefficient	t-statistics	coefficient	t-statistics
<b>Hot Money(-1)</b>	0.136061	<i>1.10504</i>	0.017961	<i>2.56495</i>
<b>Stock Returns(-1)</b>	-0.400903	<i>-0.20407</i>	0.004269	<i>0.03821</i>
<b>Effective Fed Fund Rate(-1)</b>	5.534549	<i>0.28153</i>	1.266457	<i>1.13274</i>
<b>VIX(-1)</b>	0.516221	<i>0.2073</i>	-0.12511	<i>-0.88338</i>
<b>TED(-1)</b>	-75.83571	<i>-1.34064</i>	-3.413345	<i>-1.06101</i>
<b>Intercept</b>	15.44367	<i>0.32496</i>	4.263328	<i>1.57734</i>

**Table 8. Overall VAR Estimates on the crisis period**

The table reports the pooled coefficients estimates of one-month lagged hot money and stock returns for all the markets in my sample in aggregate over the crisis periods. Left (right) panel results are for one-month lagged hot money (stock returns) on the crisis period. The numbers in the second row (in italics) are *t*-statistics for the null hypothesis that the corresponding coefficient of hot money or stock returns is zero. The VAR coefficients and covariance matrix are estimated by OLS. The sampling frequency is monthly. The crisis period is defined from January 2007 to December 2013, and from August 2007 to December 2013, in panel A and B, respectively.

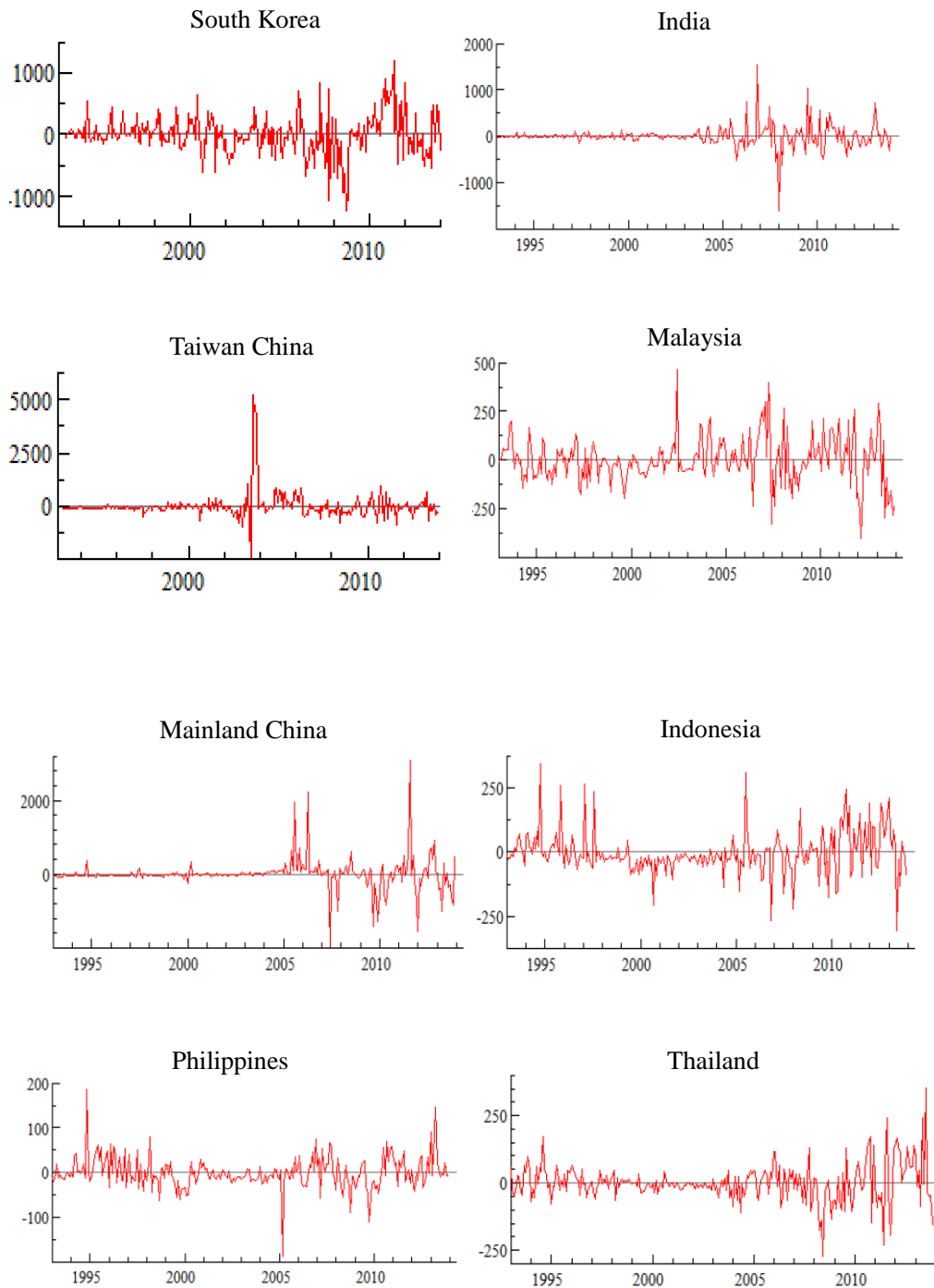
<b>Panel A</b>	<b>Hot Money</b>		<b>Stock Returns</b>	
	coefficient	t-statistics	coefficient	t-statistics
<b>Hot Money(-1)</b>	0.179488	<i>1.61331</i>	0.020864	<i>3.32071</i>
<b>Stock Returns(-1)</b>	0.654370	<i>0.35882</i>	0.149354	<i>1.45013</i>
<b>Intercept</b>	-13.57445	<i>-0.91292</i>	0.520034	<i>0.61928</i>

<b>Panel B</b>	<b>Hot Money</b>		<b>Stock Returns</b>	
	coefficient	t-statistics	coefficient	t-statistics
<b>Hot Money(-1)</b>	0.232458	<i>2.01785</i>	0.022813	<i>3.41728</i>
<b>Stock Returns(-1)</b>	0.569373	<i>0.30622</i>	0.120427	<i>1.11768</i>
<b>Intercept</b>	-11.97567	<i>-0.77806</i>	0.232629	<i>0.26081</i>

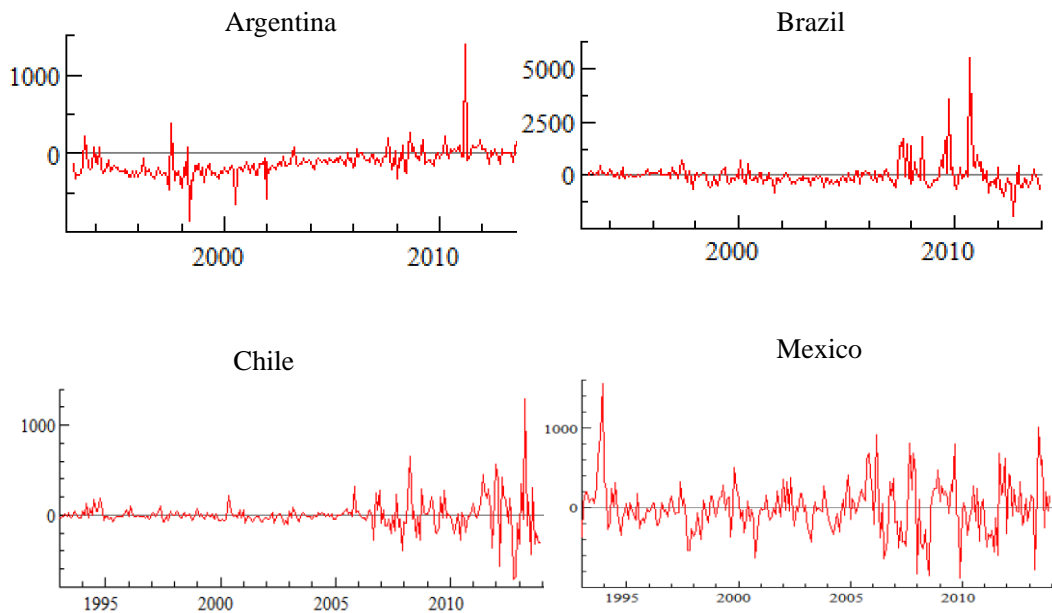
**Figure 1. “Hot Money” in Asian EMs**

The figure shows monthly hot money extracted from net equity flows for eight individual Asian EMs (South Korea, India, Taiwan China, Malaysia, Mainland China, Indonesia, Philippines, and Thailand) in current US\$ million. The sampling frequency is monthly over the period from January 1993 to December 2013.



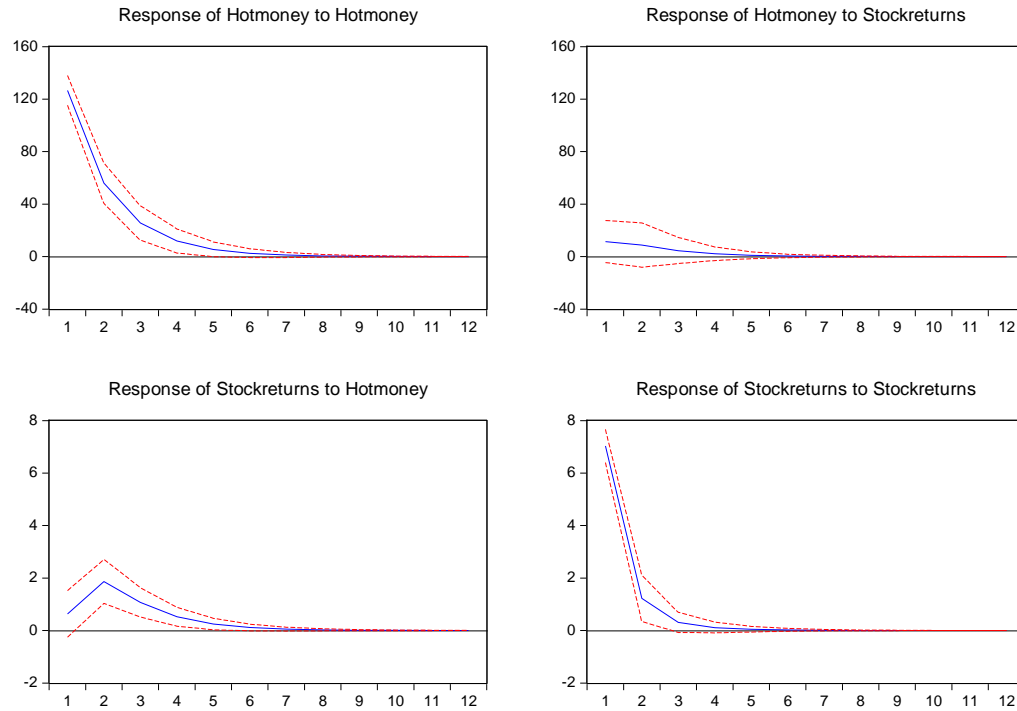
## Figure 2. “Hot Money” in Latin American EMs

The figure shows monthly hot money extracted from net equity flows for four individual Asian EMs (Argentina, Brazil, Chile, and Mexico) in current US\$ million. The sampling frequency is monthly over the period from January 1993 to December 2013.



### Figure 3. Overall Impulse Response Analysis

For all the markets in my sample, this figure plots the average generalized impulse response functions (GIRF) of hot money to one-unit standard deviation shocks to either hot money or stock returns in the above two graphs, and equity returns to one-unit standard deviation shocks to either hot money or stock returns in the below two graphs. The GIRFs are computed from the VAR coefficients reported in Table 3 over the full sample period. The vertical axis is returns in percentages and the horizontal axis is months. The solid lines are impulse response function, and the dashed line indicates double standard deviation band. The sampling frequency is monthly over the period from January 1993 to December 2013.





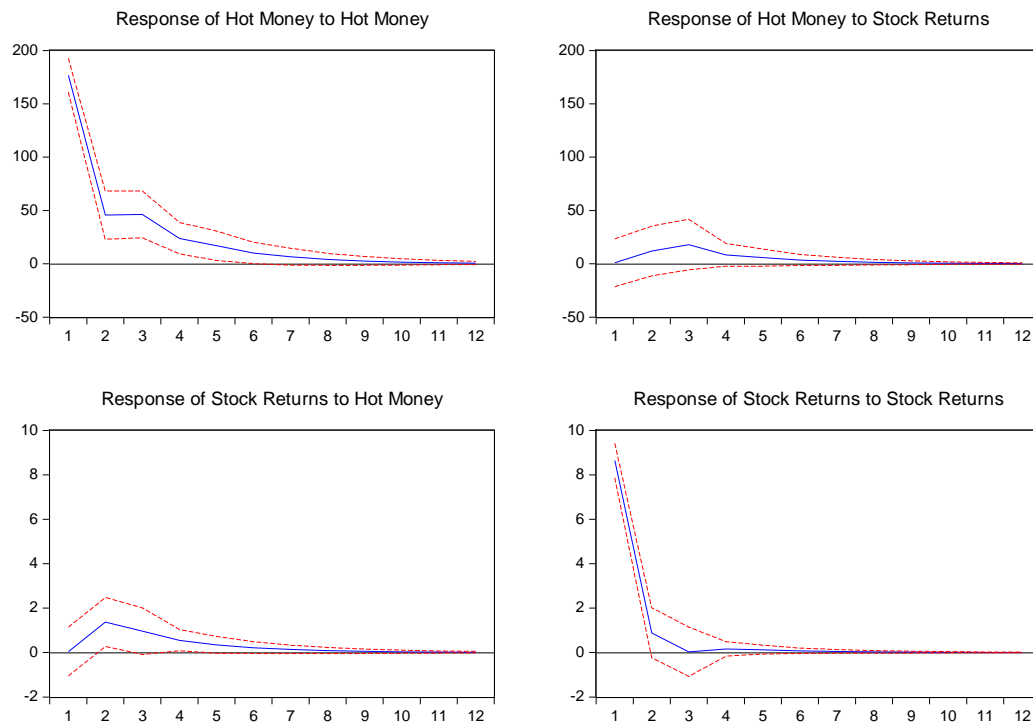
#### Figure 4. Impulse Response Analysis for the Asian Sub-group

For all the eight Asian markets in my sample, this figure plots the average generalized impulse response functions (GIRF) of hot money to one-unit standard deviation shocks to either hot money or stock returns in the above two graphs, and equity returns to one-unit standard deviation shocks to either hot money or stock returns in the below two graphs. The vertical axis is returns in percentages and the horizontal axis is months. The solid lines are impulse response function, and the dashed line indicates double standard deviation band. The sampling frequency is monthly over the period from January 1993 to December 2013.



### Figure 5. Impulse Response Analysis for the Latin American Sub-group

For all the Latin American markets in my sample, this figure plots the average generalized impulse response functions (GIRF) of hot money to one-unit standard deviation shocks to either hot money or stock returns in the above two graphs, and equity returns to one-unit standard deviation shocks to either hot money or stock returns in the below two graphs. The vertical axis is returns in percentages and the horizontal axis is months. The solid lines are impulse response function, and the dashed line indicates double standard deviation band. The sampling frequency is monthly over the period from January 1993 to December 2013.



## Appendix. State-space models

State-space models (or unobserved components model) have been widely used to estimate unobserved time variables like rational expectation, permanent income, measurement error and unobserved factors, the trend for example. Using the recursive Kalman filter algorithm, it incorporates unobserved variables (state variables) into observable models and eventually receives the estimated result. Here, state-space models enable us to measure unobserved “hot money” via decomposing the observable equity flows. The unobserved components model can be written as follows:

$$EF_{it} = \omega_{it} + v_{it} + \varepsilon_{it} \quad (1)$$

$\varepsilon_t \sim i.i.d.N(0, \sigma_{\varepsilon,i}^2)$ ,  $i=1,2,\dots,N$  are countries and  $t=1,2,\dots,T$  are months

Where  $EF_{it}$  denotes the observed equity flows from the U.S. to a given emerging market  $i$  at time  $t$ ,  $\omega_{it}$  is the unobserved permanent component of the equity flows that is considered to be a random walk process while  $v_{it} + \varepsilon_{it}$  is the unobserved temporary component that is dominated by an appropriate function, an order-two autoregressive process to be exact. The random disturbance in the system is also a set of time-dependent variables, which is represented by a white noise  $\varepsilon_{it}$ .

The general form of the permanent component is

$$\omega_{it} = \gamma + \omega_{it-1} + \delta_{it}, \quad \delta_t \sim i.i.d.N(0, \sigma_{\delta}^2) \quad (2)$$

where  $\gamma$  is the drift,  $\delta_{it}$  is a white noise part.

The general form for the temporary component is

$$v_{it} = \lambda_1 v_{it-1} + \lambda_2 v_{it-2} + \xi_{it} \quad (3)$$

Where  $\xi_{it} \sim i.i.d.N(0, \sigma_{\xi}^2)$  and coefficients satisfy:  $|\lambda_1 + \lambda_2| < 1$ ,  $|\lambda_1 - \lambda_2| < 1$ ,  $-1 < \lambda_2 < 1$

The state-space models contain two equations, one state equation, and one signal equation. The state equation reflects the state of the dynamic system at a certain moment under the effect of state variables while the signal equation (or measurement equation) connects the state vector of unobserved variables with output variables  $EF_{it}$  at some time. When the dynamic system is expressed in state space form, important algorithms with Kalman filter as the core can be applied to it. The essence of Kalman filter is to reconstruct the state vector of the system based upon the measurements.

The signal equation can be written as

$$EF_{it} = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} \omega_{it} \\ \nu_{it} \\ \varepsilon_{it} \end{bmatrix} \quad (4)$$

The state equation is

$$\begin{bmatrix} \omega_{it} \\ \nu_{it} \\ \varepsilon_{it} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \lambda_\nu & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \omega_{it-1} \\ \nu_{it-1} \\ \varepsilon_{it-1} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \omega_{it} \\ \nu_{it} \\ \varepsilon_{it} \end{bmatrix} \quad (5)$$

I use monthly CPI-scaled equity flows for each emerging market and choose Maximum Likelihood as the estimation method for recursive Kalman filter. Results produced by OxMetrics are shown in the table and graphs below. Specific to each emerging country, I have attempted the possibilities within the framework of general state-space models and choose the appropriate model according to the  $R^2$  criteria. Models for South Korea, Brazil, Malaysia, Mainland China and Indonesia are as follows:  $EF_t = \omega_t + \nu_t + \varepsilon_t$ ;  $\omega_t = \omega_{t-1} + \delta_t$ ;  $\nu_t = \lambda_1 \nu_{t-1} + \xi_t$ . The state-space model for Argentina and Chile can be written as  $EF_t = \omega_t + \nu_t + \varepsilon_t$ ;  $\omega_t = \omega_{t-1} + \delta_t$ ;  $\nu_t = \lambda_1 \nu_{t-1} + \lambda_2 \nu_{t-2} + \xi_t$ . For Taiwan China, the best specification is:  $EF_t = \omega_t + \nu_t$ ;  $\omega_t = \omega_{t-1} + \delta_t$ ;  $\nu_t = \lambda_1 \nu_{t-1} + \xi_t$ . The model I select for India, Philippines and Thailand is:  $EF_t = \omega_t + \nu_t + \varepsilon_t$ ;  $\omega_t = \gamma + \omega_{t-1} + \delta_t$ ;  $\nu_t = \lambda_1 \nu_{t-1} + \xi_t$ . Equity flows of Mexico can be decomposed using following model:  $EF_t = \omega_t + \varepsilon_t$ ;  $\omega_t = \omega_{t-1} + \delta_t$ . Q-ratios in the table measure the relative importance of the temporary and permanent components of equity flows, which are defined

as  $Q\text{-ratio}(\omega_{it}) = \frac{\sigma_{i\delta}}{\max(\sigma_{i\delta}, \sigma_{i\xi}, \sigma_{i\varepsilon})}$ ,  $Q\text{-ratio}(\nu_{it}) = \frac{\sigma_{i\xi}}{\max(\sigma_{i\delta}, \sigma_{i\xi}, \sigma_{i\varepsilon})}$  and  $Q\text{-ratio}(\varepsilon_{it}) = \frac{\sigma_{i\varepsilon}}{\max(\sigma_{i\delta}, \sigma_{i\xi}, \sigma_{i\varepsilon})}$ .  $Q\text{-ratio}(\omega_{it})$  is expected to be 1 if the variation of equity flows is mainly

derived from the dynamics of the permanent component.  $Q\text{-ratio}(\nu_{it})$  or  $Q\text{-ratio}(\varepsilon_{it})$  is supposed to be 1 if most variation of equity flows can be explained by the temporary component. For details of state-space models and Kalman filter, please refer to Sarno and Taylor (1999a, b) and Fuertes et al. (2016).